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Review:

A review of flexible job shop scheduling problems considering transportation vehicles*

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Abstract: The flexible job shop scheduling problem for processing machines and transportation vehicles (FJSP_PT) has garnered significant attention from academia and industry. Due to the inclusion of transportation vehicle scheduling in the scheduling problem of flexible manufacturing systems, solving FJSP_PT becomes more challenging and significantly more practically relevant compared to the flexible job shop scheduling problem. We summarize the assumptions, constraints, objective functions, and benchmarks of FJSP_PT. Then, statistical analysis is conducted on the literature up to 2023, including journals, number of articles published each year, and solution algorithms. We analyze recent literature on FJSP_PT, categorizing it based on algorithms into exact algorithms, heuristic algorithms, meta-heuristic algorithms, and swarm intelligence based algorithms. Finally, the research trends and challenges faced by FJSP_PT are summarized.

Key words: Flexible manufacturing system; Transportation vehicle; Processing machine; Integrated scheduling
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1 Introduction

With the upgrading of the consumption structure, the demand of markets and consumers for personalization and customization is increasing. Many countries are trying to promote the reform of manufacturing industries, such as Industry 4.0 in Germany (He YA and Xia, 2021) and Made in China 2025 (Zhang L, 2021). The traditional production mode is being changed to a more flexible and intelligent manufacturing mode to accelerate the construction of manufacturing power. With the widespread application of transportation equipment like cranes and automated guided vehicles (AGVs) (Zhang RW et al., 2024), as shown in Fig. 1, in the flexible manufacturing system (FMS), the logistics procedures transporting jobs between machines have a significant impact on production efficiency and have been considered into the job shop scheduling problem. Compared with other traditional logistics devices like conveyor belts, transportation vehicles can accomplish the logistics tasks of processing jobs in a more efficient and flexible manner.

From a theoretical standpoint, as an extension of the flexible job shop scheduling problem (FJSP) (Chen J et al., 2010; Wang HY et al., 2019), the flexible job shop scheduling problem for processing machines and transportation vehicles (FJSP_PT) is highly complex. In the production flow of a job,

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Fig. 1 Common transportation equipment in a flexible manufacturing system (FMS): (a) gantry crane; (b) automated guided vehicle

the transportation stages and the processing stages occur alternately. Correspondingly, the transportation time and the processing time together constitute the flow time of a job in FMS. In the past, most research on the traditional scheduling problem in FMS focused on the processing time and ignored the transportation time. However, flexible transportation procedures are playing more and more important roles in modern manufacturing systems. Due to the coupling between processing and transportation stages, the increase in types of scheduling entities makes solving FJSP_PT more difficult. From a practical perspective, FJSP_PT is widely found in manufacturing industries characterized by product diversification and small batches, such as the hardware and container terminal industries. Therefore, FJSP_PT represents an optimization problem that is both practically significant and theoretically intricate.

An FJSP_PT can be described as follows: In an FMS such as the one depicted in Fig. 2, there exists an order comprising N_J jobs. Each job has multiple operations to be processed. The FMS requires scheduling N_M machines and a finite number, N_A, of vehicles to effectively execute both the processing and transporting tasks for all jobs, optimizing the makespan or other related objectives. Throughout production, the transportation and processing procedures for each job will be carried out alternately. Consequently, the transportation time and processing time collectively impact the job completion duration. Therefore, FJSP_PT cannot be readily decoupled into FJSP or logistics scheduling problems. The flexibility in this problem is evident in the following areas:

1. Operation flexibility: Each operation can be processed by different machines.

2. Machine flexibility: Each machine can process multiple operations.

3. Vehicle flexibility: Each vehicle can transport all jobs for all operations.

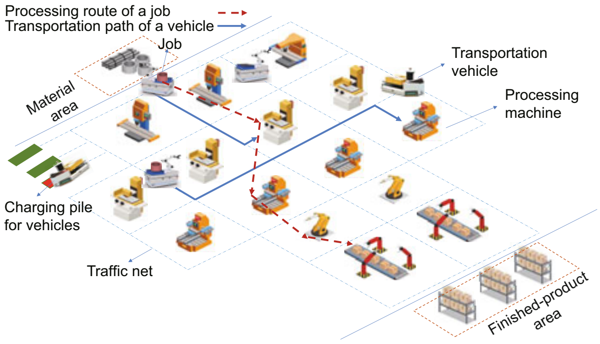


Fig. 2 Flexible manufacturing system (FMS) with transportation vehicles

Obviously, compared with other types of FJSPs, the additional vehicle flexibility in FJSP_PT will lead to an expansion of the problem solution space, increasing the difficulty of problem solving.

At present, numerous related studies focusing solely on FJSPs involving machines within FMS have been extensively conducted. The literature reviews in this domain primarily concentrate on problem analysis (Balogun and Popplewell, 1999; Rathore and Chauhan, 2015) and statistical analysis of solving algorithms such as dispatching rules (Gupta et al., 1989), genetic algorithms (GAs) (Godinho Filho et al., 2014), neural networks (Rathore and Chauhan, 2015), machine learning (Priore et al., 2001), methodologies for multiobjective optimization (Türkyılmaz et al., 2020), and others (Chan and Chan, 2004; Gao et al., 2019; Xie et al., 2019). Simultaneously, research on logistics-scheduling problems involving transportation vehicles within FMS has received attention. However, apart from Nouri et al. (2016a), there have been few reviews specifically addressing FJSP_PT. Nouri et al. (2016a) introduced a new classification schema encompassing seven criteria: number of transport sources, type of transport sources, job complexity, routing flexibility, recirculation constraints, optimization criteria, and implementation approaches. This paper aims to provide the latest overview of FJSP_PT, highlighting the following main contributions:

1. This paper summarizes the common assumptions, constraints, objective functions, benchmarks, etc., related to FJSP_PT.

2. Using bibliometric methods, this paper conducts a statistical analysis of the literature up to 2023, encompassing journals, the number of papers published each year, and solution algorithms.

3. This paper analyzes recent literature on

FJSP_PT, categorizing it based on algorithms into exact algorithms, heuristic algorithms, metaheuristic algorithms, and swarm intelligence based algorithms.

4. The research statuses, gaps, trends, and challenges of FJSP_PT are summarized.

The notations used in this paper are given in Table A1 in Appendix A.

2 Model of FJSP_PT

2.1 Problem positioning

This subsection primarily explains three scheduling subproblems essential in FJSP_PT. The typical FJSP comprises only two subproblems: job routing and operation sequencing. However, within FJSP_PT, there exists another scheduling subproblem concerning vehicles, transportation task assignment.

1. Job routing: This subproblem involves planning feasible processing routes for jobs across machines. In a flexible job shop, machines can handle various operations. Each job necessitates the processing through multiple machines to complete different operations sequentially.

2. Operation sequencing: This subproblem entails sequencing the operations to be processed on each machine. It does not affect the route of each job, but determines the processing order of operations on the same machine.

3. Transportation task assignment: In this subproblem, the transportation tasks of all operations will be allocated to different vehicles.

While FJSP_PT has been defined by the aforementioned three subproblems, it remains crucial to differentiate them from other similar problems as shown in Table 1. In Table 1, FJSP with transportation time does not schedule vehicles or does not consider their position changes during production. It includes only transportation time in makespan calculation or assumes that there are enough vehicles. Although some studies also consider vehicle path planning, this review will not cover those aspects.

Table 1 Differentiation from other similar problems

Problem	Description
Flexible job shop scheduling of machines and transportation vehicles	Including three subproblems: job routing, operation sequencing, and transportation task assignment (Zhang GH et al., 2019)
Flexible job shop scheduling with transportation time	Considering only the transportation time or enough transportation vehicle* (Dai et al., 2019)
Flexible job shop integrated scheduling and vehicle path planning problem	In addition to the above three subproblems, including the vehicle path planning problem (Saidi et al., 2015)

*When there are enough transportation vehicles, all jobs can be loaded immediately. In this case, subproblem 3 is not necessary to consider and FJSP_PT will degenerate to FJSP with transportation time

2.2 Mathematical model of FJSP_PT

Since these scheduling problems rely on the actual production context, various scholars may model them to varying extents based on specific cases. Overall, their models, such as Petri net or integer programming models, consider the following common assumptions, constraints, and objectives. In this paper, we introduce a fundamental integer programming model for minimizing makespan in Appendix A. The inclusion of transportation vehicles in FJSPs introduces numerous new assumptions, constraints, decision variables, and optimization objectives that need to be considered.

2.2.1 Common assumptions

In most literature, the following appropriate assumptions are usually made about FJSP_PT for grasping the key to the problem (Ulusoy et al., 1997; Erol et al., 2012):

1. Sufficient buffer capacity for storing unfinished/finished jobs is ensured in each machine (Chaudhry et al., 2011). Adequate space for material storage areas is typically designated during the workshop layout planning phase.

2. The consideration of machine and vehicle malfunctions is omitted (Liu et al., 2013). Equipment malfunctions, often unpredictable and challenging to control, are generally treated as sudden events and dynamically accounted for.

3. The processing and transportation durations cannot be interrupted (Kumar MVS et al., 2011). In real production scenarios, many manufacturing processes run uninterruptedly. Interruptions can

lead to decreased production efficiency, increased production costs, and potential resource wastage.

4. The loading/unloading duration of vehicles is not considered (Homayouni and Fontes, 2021). The duration is usually short and relatively stable, constituting a secondary factor in this problem.

2.2.2 Decision variables

For the mixed-integer programming model of FJSP_PT, the definitions of decision variables (Homayouni and Fontes, 2021) are as follows:

1. X_{ji}^m: If the operation O_{ji} is processed on the m^{th} machine, then $X_{ji}^m = 1$; otherwise, $X_{ji}^m = 0$.

2. $Y_{j_1 i_1, j_2 i_2}^m$: If the subsequent operation to $O_{j_1 i_1}$ on the m^{th} machine is $O_{j_2 i_2}$, then $Y_{j_1 i_1, j_2 i_2}^m = 1$; otherwise, $Y_{j_1 i_1, j_2 i_2}^m = 0$.

3. B_{ji}^m: If the operation O_{ji} is the first operation processed by the m^{th} machine, then the binary variable B_{ji}^m is set to 1; otherwise, it is set to 0.

4. L_{ji}^m: If the operation O_{ji} is the last operation processed by the m^{th} machine, then the binary variable is set to 1; otherwise, it is set to 0.

5. U_{ji}: If the transportation task O_{ji} is the first task of a vehicle, then the binary variable is set to 1; otherwise, it is set to 0.

6. R_{ji}: If the transportation task O_{ji} is the last task of a vehicle, then the binary variable is set to 1; otherwise, it is set to 0.

7. $W_{j_1 i_1, j_2 i_2}^k$: If the k^{th} vehicle transports the operation $O_{j_1 i_1}$ before $O_{j_2 i_2}$, then $W_{j_1 i_1, j_2 i_2}^k = 1$; otherwise, $W_{j_1 i_1, j_2 i_2}^k = 0$.

Here, j, j_1, and j_2 are job indexes, i, i_1, and i_2 are operation indexes, m is machine index, k is vehicle index, and O_{ji} represents the i^{th} operation of the j^{th} job. Among these variables, U_{ji}, R_{ji}, and $W_{j_1 i_1, j_2 i_2}^k$ are the new decision variables not present in FJSP.

Remark 1 Soukhal et al. (2005) investigated two-machine flow job shop scheduling problems considering transportation constraints, explicitly accounting for both transportation capacity and time. The study analyzed the complexity of this class of problems, proving the strong NP-hardness of makespan optimization. With the consideration of transportation vehicles, the solution space complexity of FJSP_PT is at least $N_{\mathrm{A}}^{N_{\mathrm{O}}}$ times higher than that of traditional FJSP, where N_{O} represents the total number of operations for all jobs.

2.2.3 Generic constraints

We summarize the common constraints of FJSP_PT from the literature as follows:

1. Processing sequence constraint: The sequence of operations for each job must adhere to a specific technological route (Deroussi, 2014), like constraints (A3) and (A4) in Appendix A. This constraint primarily stems from the inflexibility of altering the processing sequence of most jobs in the actual production.

2. Equipment utilization constraint: Machines and vehicles can handle only one job at a time (Kumar MVS et al., 2011), like constraints (A5) and (A12).

3. Job utilization constraint: Each job can only be present in a specific machine or vehicle at any time, like constraints (A16) and (A21).

4. Equipment space constraint: Machines situated in different locations result in time consumption for vehicles traveling among them, like constraints (A18) and (A21). This constraint primarily arises from the layout of machines and limitations on vehicular movement space.

5. Task logical constraint: Before each process is carried out, it needs to be transported to the designated processing machine by a vehicle, like constraints (A16) and (A21).

As shown in Appendix A, due to the transportation vehicles, constraints (A12)–(A21) are newly added or adjusted based on the FJSP model.

2.2.4 Objectives

There are numerous objectives in the literature regarding FJSP_PT for improving efficiency (about time) and stability (about workload), or reducing costs (about energy). These objective functions include makespan, mean tardiness, total weight tardiness, total workload, workload balancing, total energy consumption, and mean flow time. From another perspective, various optimization objectives can also be classified as overall metrics, machine-specific metrics, and vehicle-specific metrics, as outlined in Table 2. Over 90% of the literature on single-objective FJSP_PT adopts makespan as the objective function.

For the multiobjective FJSP_PT, green production has increasingly attracted scholars' attention (Liu et al., 2019; Zhou and Liao, 2020) in recent years. FJSP_PT problems centered around green production typically aim to minimize total energy consumption as one optimization objective, while other objectives often involve enhancing production efficiency or workload balance (Liu et al., 2019; Zhou and Liao, 2020). Commonly, in multiobjective FJSP_PT, improvements in one objective value may negatively impact other objectives, making it more challenging than solving the single-objective problem.

2.3 Benchmarks

The benchmark serves as a baseline for problem-solving and stands as a dependable standard for validating the effectiveness of algorithms. At present, there are several sets of benchmarks for FJSP_PT that are organized on the website https://fastmanufacturingproject.wordpress.com/2019/04/11/fjspt-instances/.

1. Bilge set (Bilge and Ulusoy, 1995): The 82 instances are designed at different levels of the ratio $\bar{T}_t/\bar{T}_p$ of average traveling time $\bar{T}_t$ to average processing time $\bar{T}_p$, because a major parameter influencing the interaction of the vehicle and machine schedules is the relative magnitudes of the processing time and the traveling time.

Table 2 Description of objective functions

Type	Objective function	Interpretation	Reference(s)
Overall metrics	Makespan	The time when all the jobs have been processed	Bilge and Ulusoy, 1995; Chetto et al., 1995; Ulusoy et al., 1997; Gnanavel Babu et al., 2010
	Mean flow time	The average time that all the jobs spend in FMS	Reddy BSP and Rao, 2006; Anandaraman et al., 2012
	Mean tardiness	The average difference between the completion time and the due date	Subbaiah et al., 2009; Anandaraman et al., 2012; Nageswararao et al., 2014
	Total weighted tardiness or penalty cost	The weighted sum of the difference between the completion time and the due date	Jerald et al., 2006; Poppenborg et al., 2012
	Total energy consumption	The energy consumption of all machines and vehicles	Liu et al., 2019; Wang H et al., 2021; Xin et al., 2023; Xu et al., 2023
	Profit	The ratio of profits from completed jobs within a given time to all jobs	Yung et al., 2009
Machine metrics	Total machine workload	The total working time among all machines	Liu et al., 2013
	Balancing machine workload	The standard deviation of workload among all machines	Sawik, 1996; Hoshino et al., 2008
	Machine utilization	The ratio of total machine down time to total elapsed time	Jerald et al., 2006
Vehicle metrics	Traveling time	The sum of unloading and loading time of all vehicles	Yung et al., 2009
	Distribution cost	The traveling energy-consumption cost and fixed cost of all AGVs used	Zou et al., 2021
	Vehicle utilization rate	The ratio of traveling time to elapsed time	Jerald et al., 2006
	Total waiting time	The sum of waiting time for transportation tasks	Wang XK et al., 2022
	Vehicle energy utilization	The total energy consumed by the vehicles	Yung et al., 2009

2. Deroussi set (Deroussi, 2014): The 10 instances are built by the 10 job sets and 4 layouts originally proposed in Bilge and Ulusoy (1995) and differ from the original ones in the sense that all machines have been duplicated. Thus, each operation can be performed in two alternative machines with the same processing time.

3. Kumar set (Kumar MVS et al., 2011): The 56 instances are created based on 7 job sets and 4 layouts designed by Bilge and Ulusoy (1995). Each instance in the first group has a $\bar{T}_{\mathrm{t}}/\bar{T}_{\mathrm{p}}$ ratio ≥ 0.25, whereas each instance in the second group has a $\bar{T}_{\mathrm{t}}/\bar{T}_{\mathrm{p}}$ ratio < 0.25.

4. Homayouni set 1 (Homayouni et al., 2023): This dataset comprises 20 small- and medium-sized problem instances initially designed by Fattahi et al. (2007) for the FJSP, encompassing 2–12 distinct jobs, 4–48 operations, and 2–8 machines.

5. Homayouni set 2 (Homayouni et al., 2023): This dataset comprises 10 instances proposed by Brandimarte (1993), encompassing 55–240 operations, and 21 instances designed by Chambers and Barnes (1996), with the number of operations ranging from 100 to 225.

Overall, several scholars have proposed and used benchmarks for FJSP_PT, covering various scales, $\bar{T}_{\mathrm{t}}$ and $\bar{T}_{\mathrm{p}}$.

Remark 2 The relative size of $\bar{T}_{\mathrm{t}}$ and $\bar{T}_{\mathrm{p}}$ has a significant impact on the characteristics of FJSP_PT. When $\bar{T}_{\mathrm{t}} \gg \bar{T}_{\mathrm{p}}$, the processing time of operations can be ignored and the operations on which the machines are processed are no longer critical, except for the constraints of the machines' processing capabilities. FJSP_PT will degenerate to the vehicle routing problem. When $\bar{T}_{\mathrm{t}} \ll \bar{T}_{\mathrm{p}}$, FJSP_PT will degenerate to the traditional FJSP.

3 Literature reviews for FJSP_PT

3.1 Analysis of related publications

To gain a deeper understanding of the research progress in fields related to FJSP_PT, we set the words "flexible manufacturing system," "flexible job shop," "integrated," "simultaneous," "scheduling," "automated guided vehicle," "machine," "transportation time," and "handling time" as index keywords in the Web of Science database. A statistical analysis of publications from 2000 to 2023 was conducted to highlight recent trends and directions in research within this field, as shown in Fig. 3. The statistic results and analysis are as follows:

1. As shown in Fig. 3, which is based on a topic search on three terms marked by TS1, TS2, and TS3, the number of publications researching FJSP_PT in flexible manufacturing systems increases steadily. However, compared with the whole research field of the FJSP, the research on this problem is relatively insufficient.

2. In total, nearly 100 publications have been analyzed, discussed, and synthesized until the present. *International Journal of Production Research*, *European Journal of Operational Research*, and *Computer & Industrial Engineering* published about 50% of the research articles.

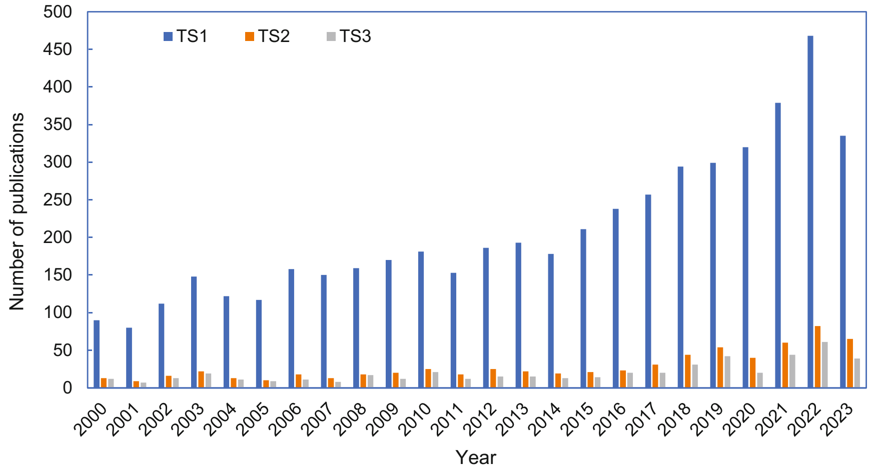
3. The proportion of publications with different methods to solve this problem is shown in Fig. 4. More than 60% of the publications focused on three approaches: neighborhood-based methods, genetic algorithms, and hybrid algorithms. The utilization of methods like artificial neural networks is comparatively low.

3.2 Methods for FJSP_PT

Within this subsection, we have provided a brief review of the relevant studies on FJSP_PT, which have also been organized into Table B1 in Appendix B. The methodologies applied to FJSP_PT are classified into three categories, i.e., exact methods, heuristics, and meta-heuristics, and presented as shown in Fig. 5. These methods will be introduced in details in the following.

3.2.1 Exact methods

Lacomme et al. (2002) tackled the simultaneous job input sequencing and vehicle dispatching problems in FMS with a single AGV system using a branch and bound approach. Further, a discrete event simulation model evaluating the job sequence given instances is built in their subsequent research (Lacomme et al., 2005). Brucker et al. (2012) addressed cyclic job shop problems with a transport robot and blocking, and presented a superior integer programming formulation to minimize the cycle time. Chikhi et al. (2015) established a mixed-integer programming model for a two-stage robotic flow job shop scheduling problem to minimize



TS1=((flexible manufacturing system OR flexible job shop) AND scheduling) AND PY=Year
TS2=((flexible manufacturing system OR flexible job shop) AND scheduling AND (AGV OR automated guided vehicle OR handling)) AND PY=Year
TS3=((flexible manufacturing system OR flexible job shop) AND scheduling AND (AGV OR automated guided vehicle OR handling) AND machine) AND PY=Year

Fig. 3 Topic search results in Web of Science

makespan and solved it using CPLEX. Heger and Voss (2017) built a new mixed-integer linear programming model for scheduling AGVs in a flexible reentrant job shop with blocking and tackled the model by GUROBI. Ham (2020) proposed two different constraint programming formulations for the first time for an FJSP with transports.

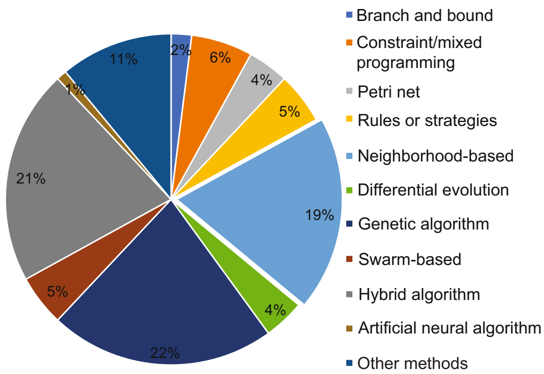


Fig. 4 Distribution of solution methods

3.2.2 Heuristics

Lee and DiCesare (1993, 1994) modeled the centralized and distributed AGV system by Petri nets for global heuristic search. Later, Chetto et al. (1995) proposed a simulation-based approach to study a dynamic scheduling problem for evaluating different dynamic scheduling strategies such as short processing time, first comes first served, and last comes first served. Sawik (1996) presented a multilevel decision model, using a bicriterion integer formulation for upper-level machine loading and part routing, and period-by-period heuristics at the lower level. Abdelmaguid and Nassef (2010) developed constructive heuristics based on Giffler and Thompson's algorithm and integrated different dispatching rules into heuristics for minimizing makespan. Zeng and Tang (2014) proposed two integer nonlinear programming models and a two-stage heuristic algorithm incorporating the timetabling method and local search, using a disjunctive graph model and feasibility principles for solving the blocking job shop problem with AGVs.

Baruwa and Piera (2016) used a timed colored Petri net (TCPN) approach for minimizing makespan and exit time objectives. The TCPN model enables the evaluation of all feasible vehicle assignments, demonstrating the benefits of vehicle-controlled assignments in certain scenarios. Tabatabaei et al. (2018) focused on both offline and dynamic scheduling problems, developing a heuristic scheduler in MATLAB. The methodology involves applying the time frame to offline problems, producing dynamic scheduling scenarios, and mathematically modeling constraints and limitations.

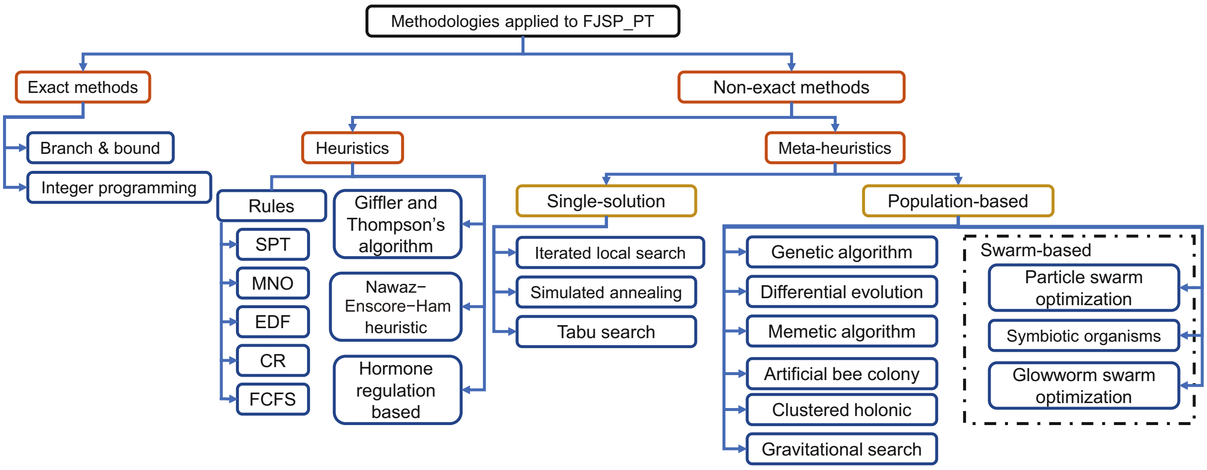


Fig. 5 Overview of research methods in the flexible job shop scheduling problem for processing machines and transportation vehicles (FJSP_PT)

Babu et al. (2018) employed the Nawaz–Enscore–Ham heuristic algorithm, analyzing 82 problems with the existing solutions for minimization of the makespan. Zheng K et al. (2018) proposed a hormone regulation based approach for online scheduling of machines and AGVs within a distributed system for assigning emergent tasks and generating feasible schedules, demonstrating improved scheduling quality compared to existing methods in real-time environments. Tang et al. (2020) proposed a hormone regulation based approach for online scheduling of machines and AGVs in a distributed system. The method assigns emergent tasks and generates feasible schedules using a task-allocation approach based on hormonal regulation.

3.2.3 Meta-heuristics

For the single-solution meta-heuristics, Ulusoy and Bilge (1993) proposed an iterative heuristic procedure where makespan is the performance criterion. Then, they built a nonlinear mixed-integer programming model, and developed an iterative procedure using the sliding time window method (Bilge and Ulusoy, 1995). Deroussi et al. (2006) combined meta-heuristic optimization and discrete event simulation to efficiently handle algorithmic and structural complexity. Further, Deroussi et al. (2008) implemented an efficient neighboring system into iterated local search, simulated annealing, and their hybridization, and demonstrated the effectiveness of the approach. Chen L et al. (2007) formulated the scheduling problem in a container terminal as a hybrid flow job shop scheduling problem with precedence and blocking constraints, with the objective of minimizing makespan, and proposed a tabu search algorithm with developed mechanisms to ensure quality and efficiency. Poppenborg et al. (2012) addressed online scheduling in a flexible job shop with blocking, aiming to minimize total weighted tardiness, using a mixed-integer programming formulation for offline scenarios and an online tabu search algorithm. Elmi and Topaloglu (2013) addressed the robotic scheduling problem in blocking hybrid flow shop cells with multiple part types, unrelated parallel machines, robots, and machine eligibility constraints. They proposed a mixed-integer linear programming model and developed a simulated annealing approach for minimizing makespan. Zheng Y et al. (2014) proposed a tabu search heuristic algorithm, featuring a two-dimensional solution representation and an innovative neighbor solution generation, to optimize makespan. Aldaihani (2015) proposed a tabu search and greedy insertion algorithm to solve the scheduling problem in flexible manufacturing cells with non-identical machines, a robot, and pallet handling.

As a highly popular and classic evolutionary optimization algorithm, GAs have been widely applied to solve this problem. Ulusoy et al. (1997) addressed the simultaneous scheduling of machines and identical AGVs in a flexible manufacturing system, minimizing makespan through a GA that uses chromosomes to represent operation sequencing and

AGV assignment dimensions, incorporating a special uniform crossover operator and mutation operators. Abdelmaguid et al. (2004) introduced a new GA with a heuristic coding scheme, combining it with selected GA operators from scheduling literature. Reddy BSP and Rao (2006) used GA based on the non-dominated sorting method and the crowding distance to minimize makespan, mean flow time, and mean tardiness, recognizing the complexity of conflicting objectives in scheduling. Jerald et al. (2006) proposed an adaptive GA to minimize the penalty cost and machine idle time. Lv et al. (2011) proposed a mathematic model based on a specific FMS with a single AGV and a single buffer area and validated it using GA with appropriate parameters. Chaudhry et al. (2011) proposed a spreadsheet-based GA to solve the problem. A domain-independent general-purpose GA was used which was an add-in to the spreadsheet software. An adaptation of the proprietary GA software was demonstrated to the problem of minimizing makespan.

Badakhshian et al. (2012) introduced a job-based GA for AGV scheduling, enhancing it with a fuzzy logic controller to control GA operators (crossover and mutation rates) during optimization. Tuma et al. (2013) explored hybridizing a GA with tabu search to potentially achieve improved results in reactive scheduling production and examined a new GA chromosome structure with a higher correlation to the makespan. Sanches et al. (2015) proposed the use of an adaptive GA for production scheduling in FMS to minimize makespan with a short running time. Zeng et al. (2015) proposed a two-stage heuristic algorithm, including a local search combined GA and a heuristic algorithm for lower makespan to solve part-scheduling problems. Umar et al. (2015) proposed a hybrid GA to optimize makespan, AGV traveling time, and penalty cost, incorporating a multi-objective fitness function with adaptive weight assignment and fuzzy expert system control of genetic operators. Lin et al. (2015) proposed a simulation optimization method and used discrete event simulation, and integrated computing budget allocation with GA for improving computational efficiency.

Nouri et al. (2016b, 2016c, 2016d, 2018) proposed hybrid meta-heuristics using a clustered holonic multiagent model, employing a neighborhood-based GA for global exploration and tabu search by cluster agents for targeted exploration. Considering the interruptions for multiple transports, Dang and Nguyen (2016) proposed a heuristic approach based on GAs to minimize the makespan. They addressed the efficient utilization of mobile robots in modern manufacturing environments and proposed a heuristic approach based on GAs to minimize the makespan. In their subsequent research, an adaptive large neighborhood search algorithm incorporating exploration/exploitation heuristics (Dang et al., 2019a) and a hybrid heuristic method combining GA and tabu search (Dang et al., 2019b) were proposed one after another.

Zhu and He (2019) proposed a novel GA to optimize production schedules and minimize makespan in manufacturing systems with shared resources. Wang M and Xin (2019) tackled the flexible flow job shop scheduling problem with parallel machines and introduced a GA with efficient coding, decoding schemes, and crossover and mutation operators. Kumar N et al. (2019) employed two heuristics, namely priority dispatching rules and modified GA with three-parent crossover, to optimize the integrated scheduling problem. Gu WB et al. (2020) used a bio-inspired scheduling optimization approach inspired by the endocrine system's hormone secretion principle. Homayouni et al. (2023) proposed an operation-based multistart biased random key GA with greedy heuristics for efficient solution generation. Wang H et al. (2021) proposed a multiobjective flexible job shop scheduling model optimizing total energy consumption and makespan. To solve this problem, they introduced a multiregion division sampling strategy based multiobjective optimization algorithm integrated with a GA and a differential evolution algorithm. Chaudhry et al. (2022) introduced a solution using Microsoft Excel spreadsheet, using the Evolver® proprietary GA for optimization. The model determines the simultaneous assignment of operations to alternative machines, sequences operations on each machine, and assigns transportation operations between machines to available AGVs. He YM et al. (2022) proposed a novel memetic algorithm combining GA and variable neighborhood search to handle dynamic events and obtain a new scheduling plan.

For the other population-based meta-heuristics, Gnanavel Babu et al. (2010) used a tackled new meta-heuristic differential evolution algorithm to solve the simultaneous scheduling of machines and two identical AGVs. Kumar MVS et al. (2011) employed differential evolution, incorporating machine selection heuristics and vehicle assignment heuristics to minimize makespan by efficiently assigning tasks to machines and vehicles. Lacomme et al. (2013) introduced a framework based on a disjunctive graph for modeling the scheduling problem and applied a memetic algorithm to minimize makespan. Nageswararao et al. proposed a hybrid meta-heuristic algorithm implemented in Java (Nageswararao et al., 2015) and a gravitational search algorithm (Nageswararao et al., 2017), aiming to optimize the sequence, relative makespan, and AGV schedule, demonstrating enhanced productivity, minimized delivery cost, and optimal fleet utilization compared to other algorithms. To maximize customer satisfaction while minimizing distribution costs, Zou et al. (2021) formulated a multiobjective mixed-integer linear programming model and developed an effective multiobjective evolutionary algorithm. The algorithm includes constructive heuristics for population initialization, a multiobjective local search for exploitation, a novel two-point crossover operator to use non-dominated solutions, and a restart strategy to prevent local optima.

He LJ et al. (2022) proposed an effective multiobjective evolutionary algorithm aimed to minimize makespan, total idle time of machines, and total energy consumption of both machines and AGVs. The algorithm incorporates an efficient encoding/decoding method, a new crossover operator, and an opposition-based learning strategy for balancing exploration and exploitation. Wang XK et al. (2022) developed a novel multi-state scheduling algorithm enhanced by neural network based travel time prediction for optimization of the AGV utilization rate and total processing makespan. The algorithm schedules more AGVs and tasks in each calculation, moving closer to global optimization. Xu et al. (2023) tackled the multiobjective green scheduling problem in integrated flexible job shops and AGVs. They introduced a multiobjective mixed-integer programming model and proposed an efficient heuristic algorithm with the population initialization method, balancing the processing time and energy consumption. Xin et al. (2025) proposed a genetic programming algorithm to make scheduling strategies evolve to solve the dynamic large-scale collaboration problem for processing machines and AGVs in FMS, and the evolving strategies had better adaptability and scalability for various scenarios.

3.2.4 Swarm intelligent methods

To minimize the makespan and total workload of machines, Liu et al. (2013) proposed a multiobjective micro artificial bee colony (MMABC) algorithm to tackle this problem, in which each solution corresponds to a food source and the bee population is divided in two parts: a replaceable bee part and a non-replaceable bee part. Nageswararao et al. (2014) proposed the binary particle swarm vehicle heuristic algorithm focusing on minimizing mean tardiness and improving solution quality. Deroussi (2014) investigated the hybridization of particle swarm optimization (PSO) with stochastic local search to experimentally determine the optimal balance between PSO's exploration ability and local search's exploitation ability, revealing that local search significantly enhances the basic PSO algorithm. Reddy KS and Reddy (2017) introduced the symbiotic organism search algorithm for simultaneous scheduling of machines and AGVs in FMS to minimize makespan, demonstrating its effectiveness through comparisons with existing methods.

Hemmati et al. (2018) addressed a flexible cell scheduling problem considering time-of-use electricity tariffs and incorporating energy-conscious policies, setup time constraints, and part defect percentages. They employed an ant colony optimization (ACO) algorithm to minimize the total cost and introduced two hybrid algorithms (hybrid GA and hybrid ACO) for improved results. Liu et al. (2019) formulated a mixed-integer programming model considering comprehensive energy efficiency. An integrated GA-GSO-GTHS algorithm, combining GA, glowworm swarm optimization (GSO), and green transport heuristic strategy (GTHS), was proposed for an efficient solution. Zhou and Liao (2020) focused on the flexible job shop greening scheduling problem with crane transportation and introduced the efficient hybrid algorithm combining particle filter and Levy flight with decomposed multiobjective evolution and PSO. Chen K et al. (2022) established a dual-resource integrated scheduling optimization model with the objective of minimizing makespan. They introduced a hybrid discrete PSO algorithm, incorporating competitive learning and a random restart mechanism to mitigate premature maturation issues. From the path- and operation-related nature of FJSP_PT, Xin et al. (2023) employed a hybrid method combining two model-based algorithms, estimation of distribution algorithm and ACO algorithm, to solve the problem. Amirteimoori and Kia (2023) proposed a mixed-integer linear programming model and a parallel hybrid PSO-GA algorithm. The novel meta-heuristic algorithm is designed for parallel computing, showcasing reduced runtime.

3.3 Real-world applications

Although FJSP_PT has been extensively studied, the practical application of these research methods is relatively limited. Dai et al. (2019) developed an enhanced genetic algorithm in terms of the makespan and the total energy consumption, and introduced a real-world case from a flexible workshop with several AGVs in Nanjing, China to demonstrate the effectiveness of the proposed algorithm. Among the Pareto solutions obtained, the most satisfying energy-efficient solution will shut down the machine with larger rate power and unloading power. He LJ et al. (2022) proposed a multiobjective scheduling model that considers sequence-dependent setup to simultaneously minimize the makespan, total idle time of machines, and total energy consumption, and developed an effective multiobjective evolutionary algorithm. A real-world intelligent manufacturing workshop integrated with AGVs for producing the components of security monitoring robots at a Chinese company was used to test the proposed algorithm. Xin et al. (2023) proposed a hybrid algorithm combining ACO and the estimation of a distribution algorithm from different problem perspectives. To validate the effectiveness, a practical case study was carried out in a hardware workshop covering a series of processes including lathing, planning, milling, cutting, bending, polishing, drilling, and spraying in the southern region of China.

4 Research statuses, trends, and future challenges

4.1 Research statuses

Based on the above content, it can be concluded that the research on FJSP_PT is relatively comprehensive, but the following statuses and gaps need to be noted:

1. From the perspective of problem modeling, many scholars have proposed various modeling methods for different types of FJSP_PT based on different practical situations. However, most scheduling problems currently have too many assumptions. Sometimes, these assumptions can reduce problem complexity and even change the nature of the problem, e.g., when there are a sufficient number of transportation vehicles. In addition, the constraint-handling is relatively simple, and scheduling objective functions focus mainly on minimizing completion time. Optimization objectives for each scheduling entity are considered less.

2. From the perspective of solution methods, a wide range of solution methods have been proposed, from exact algorithms such as branch and bound to hybrid evolutionary algorithms. However, most algorithms currently are designed based on further adaptation and improvement of FJSP-solving algorithms, lacking in-depth analysis of problem characteristics and operator design based on problem features. Furthermore, currently, the majority of solution methods are relatively classical. Approaches such as neural networks and reinforcement learning are less commonly designed and used.

3. From the perspective of experimental design, several sets of instances have been proposed. The differences among these instances primarily manifest in scale, lacking specialized design for different values of key problem parameters. However, these values such as the processing time and energy consumption of processing machines and transportation vehicles in flexible manufacturing systems may be different significantly. The magnitude of this difference (e.g., $\bar{T}_{\mathrm{t}}/\bar{T}_{\mathrm{p}}$) is highly likely to affect the solution effectiveness of algorithms. Therefore, there is an urgent need to enrich the test instances.

4. From the perspective of practical application, FJSP_PT is widely present in industries such as manufacturing and logistics management, and many solution methods have been proposed. However, they have not yet been widely applied in practice. To some extent, the scheduling of processing machines and transportation equipment depends on the workshop-production management mode. The practical application of algorithms requires scholars to consider more comprehensive and detailed factors in problem modeling. In some cases, it may even require integration with methods such as data mining and big data technology to ensure the effectiveness

and robustness of algorithms in addressing practical problems.

In addition, the implementation of these approaches imposes the following additional demands on workshop management: (1) Coordination: ensuring coordinated operation between machines and vehicles to maximize the smoothness of manufacturing systems. (2) Real-time monitoring: it is essential to monitor the production process and equipment status, including vehicle battery level, in real time, promptly adjusting scheduling strategies to respond to unforeseen circumstances. (3) Safety: ensuring that scheduling schemes comply with safety standards to avoid equipment conflicts, material accumulation, or other safety risks. (4) Data support: establishing a comprehensive data collection and analysis system to enable decision-making and optimize scheduling based on accurate production data.

4.2 Research trends

In future research on FJSP_PT, the following trends are worth paying attention to:

1. Small scale to large scale: With the diversification of market demand and the flexibility improvement of processing machines, the factory scale and order scale will increase significantly. Therefore, the scheduling problem with more processing machines and more jobs is of practical significance. Due to the advantages of low cost, high reliability, and high efficiency during operation, more and more intelligent vehicles like AGVs will be widely applied to intelligent workshops. The integrated scheduling problem with large-scale transportation vehicles also needs to be paid attention to.

2. Centralized to distributed: In the future, machines will possess more powerful perception, communication, and computing capabilities, which make distributed collaboration possible. The distributed collaboration among machines can reduce the dependence on the centralized control and bring stronger scalability and robustness. Besides, the local communication during distributed collaboration requires a lower bandwidth and fewer computing resources than centralized scheduling. Distributed collaboration also does well in dealing with local conflicts, such as vehicle fault or the temporary changes of orders. The above advantages will be more obvious in large-scale integrated scheduling problems.

3. Single objective to multiple objectives: Most of the production problems can hardly be evaluated by only one objective. To achieve low carbon and green production, a scheduling scheme considering both economic and social benefits needs to be made. Therefore, the multiobjective FJSP_PT needs to be studied. Besides, the integrated scheduling problem for machines and vehicles may be optimized based on the two kinds of objectives, such as minimizing the total workload for machines and minimizing the movement time for vehicles. Due to the coupling between the processing and transport stages, the integrated scheduling problem needs to be solved to improve their objectives simultaneously.

4. Certain to uncertain: Many uncertain factors and events exist widely in the actual manufacturing system, such as inaccurate processing time of machines, an urgent order, and even the sudden failure of a vehicle. An efficient scheduling system must be able to make a rapid and accurate response to these uncertain factors and events, so as to ensure the smooth production by adjusting the production plan quickly.

4.3 Future challenges

With further research on the problem, the following difficulties and challenges may be encountered in the solving process:

1. Large-scale FJSP_PT: Because FJSP_PT is NP-hard, the difficulty of solving this problem increases sharply with the increase of the problem scale. Exact algorithms and some swarm intelligence optimization algorithms can hardly find an acceptable solution in a tolerable time. More efficient algorithms need to be designed. Further, some specific conditions which hardly occur in small-scale FJSP_PT may no longer be ignored. For example, the vehicle-congestion problem in large-scale cases will significantly affect the operation efficiency of the workshop. From the aspects of problem characteristics and algorithm feasibility, the large-scale integrated scheduling problem needs to be re-examined.

2. FJSP_PT with complex constraints: In FJSP_PT, due to the strong dependency on vehicles, the influence and constraint relationships among different machines and even the workshopenvironment become more complex. For example, the operation sequencing of machines may be sensitive to the result of task assignment and path planning

of vehicles, not to mention that the arrival of jobs for each machine may be affected by many dynamic factors such as vehicle failures, capacity loss, and traffic congestion. Obviously, the dependence implied in the processing–transport two-phase flow must be well handled before a feasible and even robust schedule can be made. From another viewpoint, the problem knowledge brought by constraints can also be used in the generation of a desirable and even optimal schedule.

3. Dynamic FJSP_PT: In a complex workshop environment, many dynamic factors exist, such as vehicle failure and order change. Due to the obvious differences in the type, frequency, and mode of their influences on production, these factors usually need different mechanisms and methods to handle, such as the task reassignment and path re-planning for vehicle failures and the local re-scheduling for order change. Generally, rapid and accurate response is the basic requirement for dynamic processes, which creates the demands on anytime algorithms being able to provide satisfactory solutions in real time. The stability of re-scheduling is also a necessity for the safety and smoothness of production.

4. Multiobjective FJSP_PT: At present, the scheduling strategies for multiobjective optimization problems remain very challenging. The selection of appropriate objectives with diverse demands from production efficiency, safety, and comprehensive cost is still a crucial issue for FJSP_PT modeling, especially under the worldwide appeal of reducing carbon emission. Obviously, the intelligent and flexible scheduling in FJSP_PT relies on well-balanced decision-making about multiple objectives from various aspects as well as the coordination of the local objectives about the operations of machines and vehicles.

Contributors

Sai LU designed the research, processed the data, and drafted the paper. Bin XIN, Qing WANG, and Fang DENG helped organize the paper. Sai LU revised and finalized the paper.

Conflict of interest

Bin XIN is a corresponding expert of *Frontiers of Information Technology & Electronic Engineering*, and he was not involved with the peer review process of this paper. All the authors declare that they have no conflict of interest.

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Appendix A: Integer programming model of FJSP_PT

The variable notations of FJSP_PT are shown in Table A1.

Table A1 Description of key symbols

Symbol	Description	Symbol	Description
N_{J}	The number of jobs to be processed	N_{M}	The number of machines in FMS
N_{A}	The number of AGVs in FMS	J	The index set of jobs, $J=\{1,2,...,N_{\mathrm{J}}\}$
j	Index of the j^{th} job, $j\in J$	M	The index set of machines, $M=\{1,2,...,N_{\mathrm{M}}\}$
m	Index of the m^{th} machine, $m\in M$	A	The index set of AGVs, $A=\{1,2,...,N_{\mathrm{A}}\}$
k	Index of the k^{th} AGV, $k\in A$	N_j^{opr}	The total number of operations of job j, $j\in J$
N_{O}	The total number of all the operations, $N_{\mathrm{O}}=\sum_{j=1}^{N_{\mathrm{J}}}N_j^{\mathrm{opr}}$	O_j^{opr}	The index set of operations of job j, $O_j^{\mathrm{opr}}=\{1,2,...,N_j^{\mathrm{opr}}\}$, $j\in J$
O_{ji}	The i^{th} operation of job j, $i\in O_j^{\mathrm{opr}}$	LU	The initial area index of all jobs and vehicles
Ω_{ji}	The index set of machines which can handle O_{ji}	t_{jim}^{P}	The processing time of O_{ji} on machine m, $m\in\Omega_{ji}$
D	The position index set of the raw material area and machines, $D=\{0,1,...,N_{\mathrm{M}}\}$	D_d	The d^{th} position, $d\in D$. D_0 means the position of raw material and machine $m\in M$ is located at D_m
$t'_{d_1d_2}$	The unloading time between two positions, $\forall d_1,d_2\in D$	$t_{d_1d_2}$	The transportation time between two positions, $\forall d_1,d_2\in D$
T_{ji}^{et}	The ending time of the transportation stage for O_{ji}	T_{ji}^{ep}	The ending time of the processing stage for O_{ji}

The integer programming model is formulated as follows:

$$\text{Minimize } C_{\max} \tag{A1}$$

s.t.

$$C_{\max} \geq T^{\text{ep}}_{jN_j^{\text{opr}}}, \forall j \in J, \tag{A2}$$

$$\sum_{i_1<i\in O_j^{\text{opr}}} \sum_{m\in M} Y^m_{ji_1,ji} + \sum_{j_1\in J\setminus\{j\}} \sum_{i_1\in O_{j_1}^{\text{opr}}} \sum_{m\in M} Y^m_{j_1i_1,ji} + \sum_{m\in M} B^m_{ji} = 1, \forall j \in J, i \in O_j^{\text{opr}}, \tag{A3}$$

$$\sum_{i_1>i\in O_j^{\text{opr}}} \sum_{m\in M} Y^m_{ji_1,ji} + \sum_{j_1\in J\setminus\{j\}} \sum_{i_1\in O_{j_1}^{\text{opr}}} \sum_{m\in M} Y^m_{j_1i_1,ji} + \sum_{m\in M} L^m_{ji} = 1, \forall j \in J, i \in O_j^{\text{opr}}, \tag{A4}$$

$$\sum_{j\in J} \sum_{i\in O_j^{\text{opr}}} B^m_{ji} \leq 1, \forall m \in M, \tag{A5}$$

$$\sum_{j_1\in J} \sum_{i_1\in O_j^{\text{opr}}} L^m_{j_1i_1} \leq \sum_{j_2\in J} \sum_{i_2\in O_{j_2}^{\text{opr}}} B^m_{j_2i_2}, \forall m \in M, \tag{A6}$$

$$Y^m_{j_1i_1,j_2i_2} \leq X^m_{j_1i_1}, \forall j_1, j_2 \in J, i_1 \in O_{j_1}^{\text{opr}}, i_2 \in O_{j_2}^{\text{opr}}, m \in M \text{ (if } j_1 = j_2, i_2 > i_1), \tag{A7}$$

$$Y^m_{j_1i_1,j_2i_2} \leq X^m_{j_2i_2}, \forall j_1, j_2 \in J, i_1 \in O_{j_1}^{\text{opr}}, i_2 \in O_{j_2}^{\text{opr}}, m \in M \text{ (if } j_1 = j_2, i_2 > i_1), \tag{A8}$$

$$B^m_{j_1i_1} \leq X^m_{j_1i_1}, \forall j_1 \in J, i_1 \in O_{j_1}^{\text{opr}}, m \in M, \tag{A9}$$

$$L^m_{j_1i_1} \leq X^m_{j_1i_1}, \forall j_1 \in J, i_1 \in O_{j_1}^{\text{opr}}, m \in M, \tag{A10}$$

$$\sum_{m\in M} X^m_{ji} = 1, \forall j \in J, i \in O_j^{\text{opr}}, \tag{A11}$$

$$\sum_{j\in J} \sum_{i\in O_j^{\text{opr}}} U_{ji} \leq N_{\text{A}}, \tag{A12}$$

$$\sum_{j\in J} \sum_{i\in O_j^{\text{opr}}} R_{ji} = \sum_{j\in J} \sum_{i\in O_j^{\text{opr}}} U_{ji}, \tag{A13}$$

$$U_{ji} + \sum_{i_1\in O_j^{\text{opr}}, i_1<i} W^k_{ji_1,ji} + \sum_{j_2\in J\setminus\{j\}} \sum_{i_2\in O_{j_2}^{\text{opr}}} W^k_{j_2i_2,ji} = 1, \forall j \in J, i \in O_j^{\text{opr}}, k \in A, \tag{A14}$$

$$R_{ji} + \sum_{i_1\in O_j^{\text{opr}}, i_1>i} W^k_{ji_1,ji} + \sum_{j_2\in J\setminus\{j\}} \sum_{i_2\in O_{j_2}^{\text{opr}}} W^k_{j_2i_2,ji} = 1, \forall j \in J, i \in O_j^{\text{opr}}, k \in A, \tag{A15}$$

$$T^{\text{ep}}_{ji} - T^{\text{et}}_{ji} - t^{\text{P}}_{jim} \geq M(X^m_{ji} - 1), \forall j \in J, i \in O_j^{\text{opr}}, m \in M, \tag{A16}$$

$$T^{\text{ep}}_{j_1i_1} - T^{\text{ep}}_{j_2i_2} - t^{\text{P}}_{jim} \geq M(Y^m_{j_2i_2,ji} - 1), i_1 \in O_{j_1}^{\text{opr}}, i_2 \in O_{j_2}^{\text{opr}}, m \in M \text{ (if } j_2 = j_1, i_1 > i_2), \tag{A17}$$

$$T^{\text{et}}_{ji} - T^{\text{ep}}_{j(i-1)} - t_{m'm} \geq M(X^m_{ji} + X^{m'}_{j(i-1)} - 2), \forall j \in J, i \in O_j^{\text{opr}}\setminus\{1\}, m, m' \in M, \tag{A18}$$

$$T^{\text{et}}_{j1} - t_{\text{LU}m} \geq M(X^m_{ji} + U_{j1} - 2), \forall j \in J, m \in M, \tag{A19}$$

$$\begin{gathered} T^{\text{et}}_{j_1i_1} - T^{\text{et}}_{j_2i_2} - t_{m''m'} - t_{m'm} \geq M(W^k_{j_2i_2,j_1i_1} + X^m_{j_1i_1} + X^{m'}_{j_1(i_1-1)} + X^{m''}_{j_2i_2} - 4), \\ \forall j_1, j_2 \in J, i_1 \in O_{j_1}^{\text{opr}}, i_2 \in O_{j_2}^{\text{opr}}\setminus\{1\}, k \in A, m, m', m'' \in M \text{ (if } j_1 = j_2, i_1 > i_2), \end{gathered} \tag{A20}$$

$$\begin{gathered} T^{\text{et}}_{j_11} - T^{\text{et}}_{j_1i_1} - t_{m'\text{LU}} - t_{\text{LU}m} \geq M(W^k_{j_2i_2,j_11} + X^m_{j_11} + X^{m'}_{j_2i_2} - 3), \\ \forall j_1, j_2 \in J, j_2 \neq j_1, i_2 \in O_{j_2}^{\text{opr}}, m, m' \in M, k \in A \end{gathered} \tag{A21}$$

$$B^m_{ji}, L^m_{ji}, X^m_{ji} \in \{0, 1\}, \forall j \in J, i \in O_j^{\text{opr}}, m \in M, \tag{A22}$$

$$Y^m_{j_2i_2,j_1i_1}, W^k_{j_2i_2,ji}, U_{j_2i_2}, R_{j_2i_2} \in \{0, 1\}, \forall j_1, j_2 \in J, i_1 \in O_{j_1}^{\text{opr}}, i_2 \in O_{j_2}^{\text{opr}}, k \in A, \tag{A23}$$

$$C_{\max}, T^{\text{ep}}_{ji}, T^{\text{et}}_{ji} \geq 0, \forall j \in J, i \in O_j^{\text{opr}}, m \in M, \tag{A24}$$

where M is a sufficiently large positive integer. Expression (A1) ensures that the optimization objective is to minimize the makespan, and inequality (A2) ensures its proper valuation related with the completion time of all jobs. Constraints (A3) and (A4) ensure that each operation has exactly one predecessor and one successor, except for the first and last operations of each machine. Constraint (A5) ensures that each machine has at most one first operation, while constraint (A6) ensures that each machine has an equal number of first and last operations. Constraints (A7) and (A8) ensure that consecutive operations on a machine are assigned to the same machine, constraints (A9) and (A10) ensure that the first and last operations of each machine are assigned to the corresponding machine, and constraint (A11) ensures that each operation is assigned to exactly one machine.

Constraints (A12) and (A13) ensure that the number of first transportation tasks does not exceed the number of available vehicles and is the same as the number of last transportation tasks. Constraint (A14) enforces that each transportation task either is the first task of a vehicle or immediately follows one and only one other transportation task, while constraint (A15) ensures that each transportation task either is the last task of a vehicle or is immediately followed by one and only one other transportation task.

Each operation can be completed only when: (1) the corresponding job arrives at the machine which is assigned to process it, and its processing time has passed, ensured by constraint (A16); (2) the previous operation on the same machine has been completed, and its processing time has passed, ensured by constraint (A17).

Regarding the arrival times of vehicles, a job can arrive at the corresponding machine and the respective transportation task can be completed only before processing its current operation, ensured by constraint (A18), unless it is the first operation of the job, in which case the job must be transported from the LU area to the machine processing its first operation, ensured by constraint (A19). It is noteworthy that constraint (A18) applies only to cases where two consecutive operations of the same job are processed on different machines because no transportation is needed when consecutive operations are processed on the same machine, and the vehicle immediately becomes idle. Additionally, if the vehicle transports another job immediately before the current job, it is required to: (1) deliver that job to the corresponding machine; (2) pick up the current job from the location of the previous operation or, if it is the first operation, from the loading area; (3) deliver it to the machine processing the current operation. This is ensured by constraints (A20) and (A21). Finally, constraints (A22)–(A24) describe the properties of the variables.

Appendix B: Literature review of FJSP_PT

Table B1 Literature review of FJSP_PT

Reference	Problem type	Objective	Method
Lee and DiCesare, 1993	Centralized and distributed AGV systems	–	Petri net for modeling centralized and distributed AGVs
Lee and DiCesare, 1994	Centralized and distributed AGV systems	Makespan	Petri net for modeling centralized and distributed AGVs
Chetto et al., 1995	Dynamic scheduling problem for machines and vehicles with constant speed	Multiple performance measures	Simulation approach for studying scheduling rules
Bilge and Ulusoy, 1995	Machines and two identical AGVs in FMS	Makespan	Nonlinear mixed-integer programming model and heuristic procedure by time windows
Sawik, 1996	Machines and identical AGVs in FMS	Machine workloads and intermachine flows of parts	Period-by-period heuristic based family of complex dispatching rules
Ulusoy et al., 1997	Limited machines and identical AGVs in FMS	Makespan	Genetic algorithm with a special uniform crossover operator and two mutation operators
Lacomme et al., 2002	Machines with finite buffer capacity and two AGVs with blocking in FMS	Makespan	Simulation-based branch-and-bound for small- and medium-sized problem
Abdelmaguid et al., 2004	Machines and two identical AGVs in FMS	Makespan	Hybrid genetic algorithm and heuristic coding scheme

To be continued

Table B1

Reference	Problem type	Objective	Method
Soukhal et al., 2005	Two-machine flow shop scheduling problem with transporters	Makespan	Complexity analysis
Lacomme et al., 2005	Machines and a single AGV	Makespan	Branch-and-bound coupled with a discrete event simulation model
Reddy BSP and Rao, 2006	Machines and two identical AGVs in FMS	Makespan, mean flow time, and mean tardiness	Hybrid multiobjective genetic algorithm
Deroussi et al., 2006	Machines and AGVs in FMS	Makespan	Integrated local search by combining metaheuristic
Jerald et al., 2006	Machines and AGVs in FMS	Penalty cost and machine idle time	Adaptive genetic algorithm
Chen L et al., 2007	Hybrid flow shop scheduling problem with precedence and blocking constraints of a container terminal with quay cranes	Makespan	Tabu search
Deroussi et al., 2008	Machines and AGVs in FMS	Makespan	New solution representation based on vehicles rather than machines and iterated local search, simulated annealing and their hybridization
Hoshino et al., 2008	Multiple robots with various speeds in a fluctuating low-volume and high-mix manufacturing system	Workload balancing	A flexible and agile multi-robot manufacturing system with AGVs and product-processing robots
Mishra et al., 2009	Machines and material handling devices	Makespan	Particle swarm optimization with operation-based representation
Subbaiah et al., 2009	Machines and AGVs with constant speed	Mean makespan and tardiness	Sheep flock heredity algorithm
Yung et al., 2009	Six multi-operational machines and two AGVs in FMS	Machine utilization, profit made, AGV traveling time, and AGV energy utilization	Ant colony optimization
Gnanavel Babu et al., 2010	Machine and two identical AGVs in FMS	Makespan	Meta-heuristic differential evolution
Abdelmaguid and Nassef, 2010	Machines and multiple-load material handling equipment in JSP	Makespan	Constructive heuristic based on Giffler and Thompson's algorithm and different dispatching rules
Lv et al., 2011	Machines and a single AGV in FMS	Equipment utilization	Genetic algorithm
Kumar MVS et al., 2011	Machines and AGVs in FMS	Makespan	Machine-selection heuristic and vehicle-assignment heuristic which are incorporated in the differential evolution approach
Chaudhry et al., 2011	Machines and AGVs in FMS	Makespan	Spreadsheet-based genetic algorithm
Anandaraman et al., 2012	Machines, a single AGV, and two identical robots in FMS	Makespan, mean flow time, and mean tardiness	Sheep flock heredity algorithm and artificial immune system algorithm
Brucker et al., 2012	Machines and a single robot in a cyclic job shop problem with blocking	Cycle time	Integer programming formulation
Poppenborg et al., 2012	Machines and AGVs in a flexible job shop with blocking	Total weighted tardiness	Mixed-integer programming and online tabu search
Badakhshian et al., 2012	Machines and two identical AGVs	Makespan	Job-based GA controlled by fuzzy logic
Tuma et al., 2013	Machines and two AGVs in FMS	Makespan	Hybrid genetic algorithm with tabu search
Liu et al., 2013	Machines and AGVs in FJSP	Makespan and total workload of machines	Multiobjective micro artificial bee colony algorithm
Elmi and Topaloglu, 2013	Machines and AGVs in blocking hybrid flow shop cells	Makespan	Mixed-integer linear programming and simulated annealing
Lacomme et al., 2013	Machines and identical AGVs	Makespan	Framework based on a disjunctive graph and a memetic algorithm

To be continued

Table B1

Reference	Problem type	Objective	Method
Zeng et al., 2014	Machines and AGVs in a blocking job shop	Makespan	Two non-linear integer programming models and a two-stage heuristic algorithm
Zeng and Tang, 2014	Machines and AGVs in FMS	Makespan	Two-stage heuristic algorithm combining a timetabling method and local search
Nageswararao et al., 2014	Machines and identical AGVs in FMS	Mean tardiness	Binary particle swarm vehicle heuristic algorithm
Zheng Y et al., 2014	Machines and AGVs in FMS	Makespan	Mixed-integer linear programming model and tabu search
Deroussi, 2014	Flexible job shop problem with transport	Makespan	Hybridization of particle swarm optimization with stochastic local search
Sanches et al., 2015	Machines and AGVs in FMS	Makespan	Adaptive genetic algorithm
Zeng et al., 2015	Machines and single AGV in a cell part scheduling problem	Makespan	Two-stage heuristic algorithm consisting of a local search combined genetic algorithm and a heuristic algorithm
Umar et al., 2015	Machines and AGVs	Makespan, AGV travel time, and penalty cost	Genetic algorithm controlled by a fuzzy expert system
Chikhi et al., 2015	Three machines for two stages and a robot or a conveyor	Makespan	CPLEX
Nageswararao et al., 2015	Machines and two identical AGVs	Makespan	Hybrid meta-heuristic algorithm
Aldaihani, 2015	Non-identical parallel machines and a robot in a flexible manufacturing cell	Total completion time	Hybrid algorithm of tabu search and greedy insertion algorithm
Lin et al., 2015	Machines and identical AGVs in FMS	Makespan	Optimal computing budget allocation embedded with a genetic algorithm
Nouri et al., 2016c	Machines and a single transport robot in a job shop scheduling problem	Makespan	Hybrid meta-heuristic approach based on a clustered holonic multiagent model
Nouri et al., 2016d	Machines and transport robots in a flexible job shop scheduling problem	Makespan	Hybrid meta-heuristics based on a clustered holonic multiagent model
Nouri et al., 2016b	Machines and many robots in a job shop scheduling problem	Makespan	Hybrid meta-heuristic approach based on a clustered holonic multiagent model
Baruwa and Piera, 2016	Machines and AGVs in FMS	Makespan and exit time of the last job	Timed colored Petri net
Dang and Nguyen, 2016	Machines and mobile robots in modern manufacturing models	Makespan	Heuristic approach based genetic algorithm
Heger and Voss, 2017	Machines and multiple AGVs in a flexible reentrant job shop with blocking	Makespan	Mixed-integer linear programming and GUROBI
Nageswararao et al., 2017	Machines and two AGVs in FMS	Makespan	Meta-heuristic gravitational search
Reddy KS and Reddy, 2017	Machines and AGVs in FMS	Makespan	Symbiotic organism search
Nageswararao et al., 2017	Machines and AGVs in FMS	Completion time and mean tardiness	Meta-heuristic based on three initial scheduler algorithms
Nouri et al., 2018	Machines and single AGV in a flexible job shop scheduling problem	Makespan	Hybrid meta-heuristic approach based on a clustered holonic multiagent model
Tabatabaei et al., 2018	Machines and two identical AGVs in dynamic FMS	Cycle time	Heuristic method
Babu et al., 2018	Machines and material control devices in FMS	Makespan	Nawaz–Enscore–Ham heuristic algorithm
Zheng K et al., 2018	Machines and AGVs	Makespan	Hormone regulation based approach
Hemmati et al., 2018	Machines and AGVs in a flexible cell scheduling problem	Total cost	Hybrid genetic algorithm and hybrid ant colony algorithm

To be continued

Table B1

Reference	Problem type	Objective	Method
Dang et al., 2019a	Machines and identical AGVs	Makespan	A hybrid heuristic of genetic algorithm and tabu search
Liu et al., 2019	Machines and single crane in a flexible job shop scheduling problem	Total energy consumption and makespan	Genetic algorithm, glowworm swarm optimization, and green transport heuristic strategy
Gu WN et al., 2019	Multiple AGVs with constant speed in a dynamic AGV scheduling problem	Makespan	Biological intelligent approach
Dang et al., 2019b	Automatic machines and material handling devices	Makespan	Hybrid heuristic method combining genetic algorithm and tabu search
Zhu and He, 2019	Machines and AGVs with constant speed in modern manufacturing systems	Makespan	Average distribution genetic algorithm
Wang M and Xin, 2019	Parallel machines and identical AGVs in a flexible flow shop	Makespan	Genetic algorithm with effective coding and decoding scheme and genetic operators
Kumar N et al., 2019	Part, tool, and two automated guided vehicles in FMS	Makespan	Priority dispatching rules and a modified genetic algorithm
Gu WB et al., 2020	Machines and AGVs with constant speed in a dynamic scheduling problem	Makespan	Bio-inspired scheduling optimization approach inspired by a hormone secretion principle
Ham, 2020	Machines and identical transports in FMS	Makespan	Two constraint programming formulations
Tang et al., 2020	Machines and AGVs within a distributed online system	Makespan	Hormone regulation
Zhou and Liao, 2020	Machines and cranes for flexible job shop green scheduling	Total energy consumption and makespan	Levy flight based decomposed multiobjective evolution hybridized with particle swarm
Homayouni et al., 2023	Machines and transports in FMS	Makespan	Operation-based multistart biased random key genetic algorithm
Homayouni and Fontes, 2021	Machines and transports in FMS	Makespan	Local search
Wang H et al., 2021	Machines and transportation robots in a flexible job shop scheduling problem	Total energy consumption and total makespan	Multi-region division sampling strategy based multiobjective optimization algorithm integrated with a genetic algorithm and a differential evolution algorithm
Zou et al., 2021	Machines and AGVs in a matrix manufacturing workshop	Overall customer satisfaction and distribution costs	Effective multiobjective evolutionary algorithm with local search
He LJ et al., 2022	Machines and AGVs in a job shop environment	Makespan	Effective multiobjective evolutionary algorithm with a new crossover operator
Chaudhry et al., 2022	Machines and AGVs in a flexible job shop environment	Makespan	Genetic algorithm based on a spreadsheet model
Chen K et al., 2022	Machines and AGVs in a flexible job shop environment	Makespan	Hybrid discrete particle swarm optimization algorithm with a heuristic initialization method
He YM et al., 2022	Machines and robots in a flexible job shop	Makespan	Novel memetic algorithm combining genetic algorithm and variable neighborhood search
Wang XK et al., 2022	Machines and AGVs in FMS	Makespan, AGV load rate, AGV utilization, and task execution time	Multistate scheduling algorithm
Amirteimoori and Kia, 2023	Machines and AGVs in a flexible job shop system	Makespan	Parallel hybrid particle swarm optimization and genetic algorithm
Xu et al., 2023	Machines and AGVs in a mullti-objective green scheduling problem	Total energy consumption and makespan	Efficient heuristic algorithm with a greedy insertion decoding method considering the selection of AGVs
Xin et al., 2023	Machines and AGVs in FMS	Total energy consumption and makespan	Genetic programming